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WEAR RATE PREDICTION OF FRICTION STIR WELDED DISSIMILAR ALUMINUM ALLOY BY ANN

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ABSTRACT

The effect of process parameters on the mechanical properties of dissimilar AA6061 t6–AA5083 0 joints produced by friction stir welding was studied. Different samples were produced by varying the advancing speeds of the tool as 20 and 40 mm/min and by varying the alloy positioned on the advancing side of the tool. The rotating speed is varied from 600 to 900 rpm. Taking all these above-mentioned points into consideration, it is obvious that the relationship between these parameters has to be established in order to understand their interdependencies. Artificial neural networks possess such predictive capabilities, when trained, to understand the relationship between the dependent and independent variables of the system. This work involves a neural network with 4 independent variables. The aim is to train the network so that it will be able to predict with reasonable accuracy. In order to use the network for prediction, it must show the least possible root mean square error during validation.

KEYWORDS: ANN, Wear Rate, FSW & Backpropagation Algorithm

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Original Article

INTRODUCTION

Friction Stir Welding (FSW) is a solid-state welding process where metals join in the plastic state, hence the absence of melting of the metals. [1][2]. A major source of heat is due to the friction originating from the workpiece and too [3] Softened material then flows from the back of the tool to the front, thus creating joints [4]With the development of new tool materials high melting point metals also can be joined using FSW [5]. The process parameters included tool rotational speed, welding speed, axial force and the tool pin profile affected the welded joints [6] [7] A close match between the optimized values and the experimentally determined values. Was observed [8] ANN is adapted to establish a correlation between the FSW parameters. The developed mathematical model was used to predict mechanical characterization of welded Al properties as an outcome rotational speed and welding speed. [9].

NETWORK ARTIFICAL NEURAL

Artificial Neural network mimics the human brain or neural system activities such as information processing. Neurons serve as basic elements of the neural network. These neurons process the input signals. This processed information will generate appropriate outputs. ANN could accommodate larger input and also filter the noise and incomplete data. Network training function of ANN takes care of bias values by having gradient descent to reduce error [10]. The network is a multi-layer network which has input layer as feed and output layer which generates output response and at least one hidden layer which uses training function to

processes inputs to yield output).

The established neural network consists of four inputs as the neurons denoting the process parameters.

Hidden layers with 10-20 neurons adopted for training the data and about 3 neurons used to predict the mechanical properties of the above mentioned solid state welded dissimilar aluminum alloy.

BACKPROPAGATION ALGORITHM

The backward propagation network is a supervised learning algorithm. In this set of inputs and their corresponding outputs are trained [11] [12]. Input layer feeds the information to the hidden layer which processes the same and gives output. Accuracy of the predicted response depends on the training. The difference between the measured value and predicted value is an error here and could be measured by the Mean sum of Squared Errors (MSE). In the course of training, the error between the experimental value and predicted value is minimized by altering the weights in the network. Backward propagation further improves the altered values. This propagation continues until the error attains the acceptable level.

BACKPROPAGATION ALGORITHM

Nonlinear multilayer networks adopts back propagation

Algorithm, because it uses a gradient descent approach.[13]

Experimental acquisition of the input/output mapping is possible within multilayer networks in this algorithm.

A neural network model was made having the process parameters as input to estimate the mechanical properties such as UTS, percentage of elongation, wear rate, wear resistance as responses. The first iteration of the algorithm is to fit process inputs and their corresponding outputs from 0.1 to 0.9 by using the following relation [14] [15]

$$X = 0.8 \frac{(Z_i - Z_{min})}{(Z_{max} - Z_{min})} \times 0.1 \qquad (1)$$

Where Xi = Normalized input/output value

Zi = Actual input/output value

Zmax = Maximum input/output value

Zmin = Minimum input/ output value

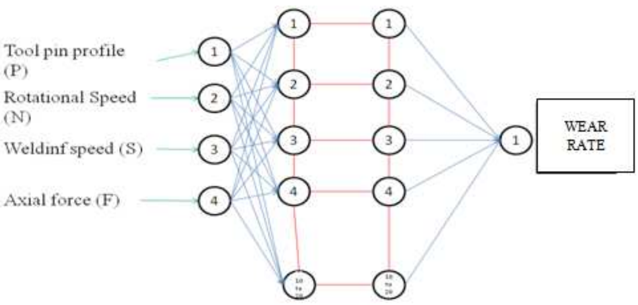

Figure 1: Neural Network Model Architecture

Figure1 shows the forward and back propagation structure. Tool pin profile, tool rotation speed, welding speed and axial force are designated as input layers in this work. Tool pin profile, tool rotational speed, welding speed and axial force are the four nodes of the input layer. These layers estimate the process outputs such as wear rate. Training of several networks is needed to determine the number of hidden layers and neurons involved in the process

DEVELOPMENT OF NEURAL NETWORK MODEL

To predict wear rate of friction stir welded dissimilar aluminum alloy, a feed-forward, back propagation neural network model was adopted. In this work MATLAB version, 7.8R2009a was co adopted as the software tool. 25 samples from experimental data omitting the last repeated 5 values were selected purely on the random method for training to develop the back propagation neural model to predict the responses.

The network has been fed with the training data and the network was adjusted according to the error. [16]. Network generalization was measured using the validated data. The training was stopped when there was a stagnation on the improvement of the generalization. The testing data had no effect on training and so provide an independent measure of network performance before and after training. The input layers had four neurons (for four input parameters) and output layer had one neuron (representing any one of the four output mechanical properties as a response). [17]. The best solution was iterated using various network structures with different number of hidden layers and different number of neurons in each hidden layer. Normalization of input and output parameters have been carried out by using the ranges of 0.1-0.9 by using the equation 1. In MATLAB command window. The function of the command neural network is to open the network manager to enable import, create, use, and export neural networks and data. Then normalized data were adopted to network/data manager.

PREDICTIVE NETWORK MODEL FOR WEAR RATE

Figure 3 shows the feed forward three-layered back propagation network architecture arrived to predict the wear rate. By training several networks, the number of hidden layer and neurons in the hidden layer has been estimated.

Eventually 12 hidden layers and 10 neurons in each hidden layer were arriving as adequate and suitable for the model

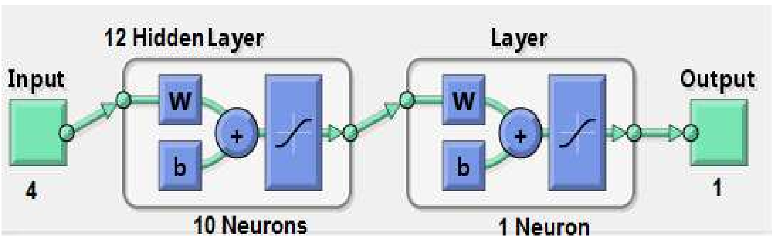

Figure 2: Neural Network Architecture to Predict Wear Rate

The network has been trained for several times by fixing 1000 epochs to arrive best validation performance. The optimum performance of mean squared error of 5.2164 x 10-6 was arrived at 210 epochs. The workspace of MATLAB was fed with the simulation results of the established network. The predicted values for wear rate of the developed network are presented in Table 1.

Table 1: Comparison of Measured and Predicted Values of Wear Rate

Trial No	FSW Process Parameters				Wear Rate		Error (%)
	P	N	S	F	Experimental Value	Predicted Value by ANN Model	
T01	-1	-1	-1	-1	446.43	456.94	2.3
T02	1	-1	-1	-1	476.19	470.08	-1.3
T03	-1	1	-1	-1	462.96	459.60	-0.73
T04	1	1	-1	-1	458.72	477.68	3.97
T05	-1	-1	1	-1	454.55	461.00	1.4
T06	1	-1	1	-1	495.05	477.62	-3.65
T07	-1	1	1	-1	471.7	465.92	-1.24
T08	1	1	1	-1	465.12	479.36	2.97
T09	-1	-1	-1	1	454.55	467.98	2.87
T10	1	-1	-1	1	502.51	501.36	-0.23
T11	-1	1	-1	1	483.09	474.55	-1.8
T12	1	1	-1	1	476.19	487.55	2.33
T13	-1	-1	1	1	467.29	489.92	4.62
T14	1	-1	1	1	512.82	501.29	-2.3
T15	-1	1	1	1	495.05	491.32	-0.76
T16	1	1	1	1	478.47	496.65	3.66
T17	-2	0	0	0	465.12	465.40	0.06
T18	2	0	0	0	497.51	494.89	-0.53
T19	0	-2	0	0	487.8	485.18	-0.54
T20	0	2	0	0	490.2	512.76	4.4
T21	0	0	-2	0	454.55	465.25	2.3
T22	0	0	2	0	465.12	466.57	0.31
T23	0	0	0	-2	456.62	457.12	0.11
T24	0	0	0	2	480.77	505.38	4.87
T25	0	0	0	0	411.52	421.12	2.28

The difference between the predicted value and experimental value is very much within the allowable level (5%). The best line of fit was arrived for training, testing, validation and overall data utilized to train a neural network, which is very much critical for accuracy.

The correlation coefficient of the predicted neural network model arrived for training, testing, validation and overall data were 1, 0.95421, 0.99051 and 0.96873 respectively. It affirms the established neural model was adequate enough to predict the output with higher accuracy

COMPARISON OF MECHANICAL PROPERTIES BY VARIOUS MODELS

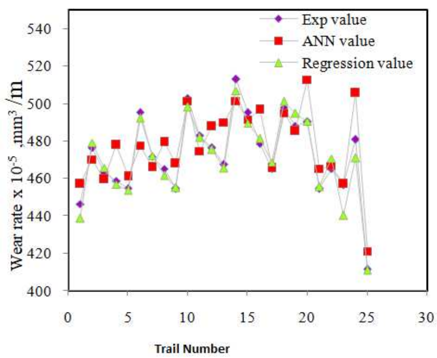

Figure 3: Comparative Graph for All the Models

The comparison of wear rate of FS welded dissimilar aluminum alloy that is obtained by regression modeling and neural network modeling are compared with experimentally measured values graphically as shown in Figure 2. Both model values were closer to experimental values

CONCLUSIONS

Artificial neural network models were developed to predict the UTS, the percentage of elongation, wear resistance and wear rate by incorporating FSW process parameters such as tool pin profile, tool rotational speed, welding speed and axial force. The developed neural networks consist of four input neurons for process parameters, 4 to 6 hidden layers consisting of 10 to 20 neurons in each layer for training the data and 1 to 3 neurons. The line of best fit and correlation coefficients between actual and predicted values for training, validation, testing and all data was obtained for UTS, the percentage of elongation, wear resistance and wear rate. The developed models were capable of predicting values with less than 5% error. The correlation coefficient between the experimental and predicted values of the developed model was in between 0.9 to 1, which shows the model developed is satisfactory. Comparison of the ANN model with regression model and the experimental value was done results shows both models are very close to experimental values.

REFERENCES

1. *W.M. Thomas, P.L. Threadgill, and E.D. Nicholas, "Friction stir welding of steel: Part one," http://steel.keytometals.com/default.aspx?ID= Check Article&NM=219.*
2. *R. Nandan, T. DebRoy, and H. Bhadeshia, "Recent advances in friction-stir welding - Process, weldment structure and properties," Progress in Materials Science, vol. 53(6), 2008, pp. 980-1023.*
3. *T.J. Lienert, W.L. Stellwag, B.B. Grimmett, and R.W. Warke, "Friction stir welding studies on mild steel - Process results, microstructures, and mechanical properties are reported," Welding Journal, vol. 82(1), 2003. pp. 1S-9S.*
4. *R. Zettler, T. Donath, J.F. Dos Santos, F. Beckman, and D. Lohwasser, "Validation of marker material flow in 4mm thick frictionstir welded Al2024-T351 through computer microtomography and dedicated metallographic techniques," Advanced Engineering Materials, vol. 8(6),2006, pp. 487-490.*
5. *C.D. Sorensen, and T.W. Nelson, "Friction Stir Welding of Ferrous and Nickel Alloys, in Friction stir welding and processing, Mahoney," ASM International: Materials Park, Ohio. 2007, pp. 111-121.*
6. *K. Elangovan, V. Balasubramanian, and S. Babu, "Predicting tensile strength of friction stir welded AA6061 aluminium alloy joints by a mathematical model," Material & Design, vol. 30 (1), 2009,pp.188-193.*
7. *S. Babu, K. Elangovan, V. Balasubramanian, and M. Balasubramanian, "Optimizating friction stir welding parameters to maximize tensile strength of AA2219 Aluminium ally joints," Metals and Materials International, vol. 15(2), 2009, pp. 321-330.*
8. *A.K. Lakshminarayanan, and V. Balasubramanian, "Process parameters optimization for friction stir welding of RDE- 40 aluminium alloy using Taguchi technique," Transactions of Nonferrous Metals Society of China, vol. 18 (3), 2008, pp. 548-554.*
9. *M. Jayaraman,R. Sivasubramanian,V. Balasubramanian, and A.K. Lakshminarayanan, "Optimization of process parameters for friction stir welding of cast aluminium alloy A319 by Taguchi method," Journal of Scientific & Industrial Research, vol 68 (1), 2009. pp. 36-43.*

10. *H. Okuyucu, A. Kurt, and E. Arcaklioglu, "Artificial neural network application to the friction-stir welding of aluminum plates," Materials & Design, vol. 28 (1), 2007, pp. 78- 84.*
11. *T. Ozel and Y. Karpat, Predictive modelling of surface roughness and tool wear in hard turning using regression and neural networks, International Journal of Machine Tools & Manufacture 45 (2005) 467–479.*
12. *Surjya K. Pal and DebabrataChakraborty, Surface roughness prediction in turning using artificial neural network, Neural Computing & Applications Volume 14, Number 4 / December, 2005 319-324*
13. *Vishy Karri, F. Frost, "Optimum Back Propagation Network Conditions With Respect To Computation Time and Output Accuracy," iccima, p. 50, Third International Conference on Computational Intelligence and Multimedia Applications (ICCIMA'99), 1999.*
14. *Sreeraj, P., T. Kannan, and Subhasis Maji. "Prediction and optimization of weld bead geometry in gas metal arc welding process using RSM and fmincon." Journal of mechanical engineering research 5.8 (2013): 154-165.*
15. *Huang, S.H. Hong-Chao Zhang, Artificial neural networks in manufacturing: concepts, applications, and perspectives, Components, Packaging, and Manufacturing Technology, Part A, IEEE Transactions, Volume: 17, Issue: 2 212-228.*
16. *E. WESTKÄMPER and T. Schmidt, Computer-assisted manufacturing process optimization with neural networks, Journal of Intelligent Manufacturing, Volume 9, Number 4 / August, 1998 289-294.*
17. *ValluruRao and HayagrivaRao, C++ Neural Networks and Fuzzy logic.*
18. *Jiawei Han, MichelineKamber, Data Mining Concept and Techniques, Morgan Kaufman Publishers, 2002.*